RUNNING HEAD: A MEASURE OF SEARCH EFFICIENCY

A Measure of Search Efficiency in a Real World Search Task

Melissa R. Beck[1], Maura C. Lohrenz[2], J. Gregory Trafton[3]

[1]Louisiana State University

[2]Naval Research Laboratory, Stennis Space Center, MS

[3]Naval Research Laboratory, Washington DC

UNDER REVIEW: DO NOT CITE WITHOUT PERMISSION

Please address correspondence to

Melissa R. Beck

Louisiana State University

Psychology Department

236 Audubon Hall

Baton Rouge, LA 70808

(225) 578-7214

mbeck@lsu.edu

REPORT DOCUMENTATION PAGE	Form Approved OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*	2. REPORT TYPE	3. DATES COVERED *(From - To)*
19-12-2008	Final Performance Technical Report	From 02-22-07 to 09-30-07

4. TITLE AND SUBTITLE

A Measure of Search Efficiency in a Real World Search Task

5a. CONTRACT NUMBER N00173-07-1-G901

5b. GRANT NUMBER NRL BAA 07-08, 55-07-01

5c. PROGRAM ELEMENT NUMBER 0602782N

6. AUTHOR(S)

Beck, Melissa R. Ph.D (LSU)
Maura C. Lohrenz (NRL Code 7440.1)
J. Gregory Trafton (NRL Code 5515)

5d. PROJECT NUMBER 08294

5e. TASK NUMBER

5f. WORK UNIT NUMBER 9600

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

Louisiana State University
Office of Bursar Operations
125 Thomas Boyd Hall
Baton Rouge LA 70803-2804

8. PERFORMING ORGANIZATION REPORT NUMBER

LSU Proposal #31847

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

Naval Research Laboratory
Code 7440.1
Stennis Space Center, MS 39529-5004
Attn: Maura C. Lohrenz (Bldg. 1005, Room D22)

10. SPONSOR/MONITOR'S ACRONYM(S)

NRL SSC

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

NRL/JA/7440-08-1009

12. DISTRIBUTION/AVAILABILITY STATEMENT

Approved for Public Release, distribution is unlimited.

13. SUPPLEMENTARY NOTES

Submitted to the journal "Perception" (currently under review).

14. ABSTRACT

In visual search, preattentive processes locate potential target regions and selective attention is directed to potential target locations. The current experiments examined the role of global visual clutter in participants' ability to deploy attention to target regions containing relatively more or less local clutter. Participants searched maps of high, medium, or low global clutter for a target in a high or low local clutter region. Global and local clutter influenced search time, with larger effects of local clutter as global clutter increased. In addition, there was no effect of set size on search time. We propose that the preattentive process of detecting regions likely to contain the target is less efficient as the amount of global clutter increases. Furthermore, in complex images and real world search tasks, global and local clutter measures can provide a good predictor of search efficiency when search set size is difficult to determine.

15. SUBJECT TERMS

Clutter, displays, visual search

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
U	U	U	UU	24	Melissa R. Beck
					19b. TELEPHONE NUMBER *(Include area code)* (225) 578-7214

Abstract

In visual search, preattentive processes locate potential target regions and selective attention is directed to potential target locations. The current experiments examined the role of global visual clutter in participants' ability to deploy attention to target regions containing relatively more or less local clutter. Participants searched maps of high, medium, or low global clutter for a target in a high or low local clutter region. Global and local clutter influenced search time, with larger effects of local clutter as global clutter increased. In addition, there was no effect of set size on search time. We propose that the preattentive process of detecting regions likely to contain the target is less efficient as the amount of global clutter increases. Furthermore, in complex images and real world search tasks, global and local clutter measures can provide a good predictor of search efficiency when search set size is difficult to determine.

Evidence of a Two-Stage Model of Visual Search in a Real World Search Task

Visual search tasks, such as finding the milk in the refrigerator or a destination on a map, are performed repeatedly in our every day lives. Not only is visual search a common daily task, but it has also proved to be a useful tool in determining how the visual system processes visual information (see Wolfe, 1998 for a review). This has mainly been due to the use of highly controlled and artificial stimuli. However, with the advance of theories in this area of research, it is becoming increasingly important to examine the extent to which these theories are applicable to more real world situations. The current paper demonstrates that local and global visual clutter provide evidence for a two-stage theory of visual search in real world search tasks.

The predominant theoretical view is that visual search takes place in two stages. Treisman and Gelade (1980) proposed that basic features are identified in parallel and then selective attention binds these features into objects serially. Wolfe's Guided Search model adds that the preattentive stage guides selective attention toward items that are likely candidates for the target (Wolfe, 1994; Wolfe, 2007). Evidence for a two-stage theory was gained by examining the slope of the reaction time (RT) by set size function while varying the similarity between targets and distractors. When the search target differs from the distractors by a feature available to the preattentive processes (e.g., color, orientation, etc.), search is completed in parallel and the slope of the RT by set size function is close to zero. However, if the target is similar to the distractors, items compete for selective attention and RTs increase as the number of distractors increase. This

increase in RTs demonstrates the role of the serial, selective attention process in identifying items in more complex search tasks.

Single stage, parallel models of search can also lead to an increasing RT by set size function (Busey & Palmer, 2008; Palmer et al., 1993; Thornton & Gilden, 2007; Townsend, 1974). According to these models, the information needed to conduct the visual search task is processed by a limited capacity parallel system. The RT x set size function is predicted to increase because as more information needs to be processed, the limited recourses are spread thinner. However, support for these parallel models are generally found with simplistic stimuli of limited set sizes (around 4). As the stimuli become more complex (configuration searches – searching for an upside-down Y among right side-up Ys) the data is less likely to support these models. The stimuli used in the current studies are complex maps, and participants are searching for single-bump elevation markers among double-bump elevation markers (see Figure 1). This type of search task is typically not supported by single stage, parallel search models (Busey & Palmer, 2008), because the task requires the identification of the configuration of features, not just the identification of the conjunction of features. In addition, as in most real world search tasks, saccades are often necessary to bring potential target regions into the focus of the fovea so they can be resolved and identified. Therefore, it is unlikely that a single stage parallel model can be applicable to the search task used in the current studies.

In the traditional search tasks demonstrating an increasing RT by set size function, artificial and controlled stimuli are typically used (e.g., rotated T's and L's) on a blank background. Therefore, it is relatively straightforward to manipulate how many

distractors are present in the display and how perceptually similar the distractors are to the target. However when examining real world search tasks, it is less clear what items in the scene are competing with the target as distractors. For example, Neider and Zelinsky (2008) reported an inverse set size effect using real world scenes. Participants' task was to search for a tank among trees. As more trees were added, search time decreased. Based on the pattern of eye movements, it was concluded that increasing set size lead to perceptual grouping of items in the display, making search more efficient. This study is a demonstration of the difficulties that can arise in determining set size in real world images (e.g., what should be counted as an individual item: a single tree or a group of trees?) Given this difficulty, a goal of the current paper is to determine if a measure of visual clutter can be used in place of set size to examine the application of theories in visual search to a real world search task.

Determining the actual set size in the maps used in the current study is virtually impossible by traditional methods (e.g., counting the number of items similar to the target). Therefore, we vary the relative number of distractors across images but not the absolute number. We manipulated set size by adding to the maps 4, 8, or 16 distractors that are visually similar to the target. It could be argued that this is an arbitrary definition of set size because there could (and likely are) other visual stimuli in the map that compete for attention with the target. However, the same maps were used across all levels of set size (between subjects) and therefore, although the set size may not be strictly 4, 8, or 16, the set size in the 8-distractor images is 4 greater than in the 4-distractor images and the set size in the 16-distractor images is 8 greater than in the 8-distractor images. Therefore, although we do not necessarily know the absolute set size, we do know there

is an increase in set size. This is somewhat unsatisfying and therefore argues for developing a method other than set size for determining search efficiency in real world search tasks.

In addition to set size, several other factors impact search efficiency (distractor similarity: Duncan & Humphreys, 1989; spatial layout: Beck & Trafton, 2007; object occlusion: Bravo & Farid, 2004; background complexity: Wolfe, et al., 2002). For example, search efficiency decreases as similarity between the distractor increases (Duncan & Humphrey, 1989). A quantitative measure of visual clutter could potentially take several or all of these factors, including set size, into account. The current experiments tested the color-cluster clutter (C3) algorithm as a predictor of search efficiency. The C3 algorithm computes a clutter value based on both color saliency and color density (Lohrenz & Gendron, under review). Color density is determined by clustering all the pixels in an image according to their proximity in both location and color and calculating, for each cluster, the number of clustered pixels divided by the cluster area. Lower color density suggests greater clutter. Color saliency is calculated (for each cluster) as the color difference between the current cluster and all adjacent clusters. High color saliency in a region with low color density suggests even greater clutter. The C3 clutter value is calculated as $15(1-D) \exp(-6.3 \exp(-S/10))$, where D is color density and S is color saliency.

Color was chosen as the main feature of interest in C3 because in studies examining several potential contributing factors to clutter, color variability has been found to be an important factor in determining search efficiency (Rosenholtz, et al., 2007). The number of clusters identified can be considered an approximation of set size

and the similarity between clusters can be considered a measure of distractor similarity. Therefore, the C3 clutter rating quantifies set size, distractor heterogeneity, and background complexity.

As further support for the potential usefulness of C3 for predicting search efficency, C3 ratings are highly correlated with subjective ratings of visual clutter (Lohrenz, Trafton, Beck & Gendron, under review). Participants were asked to rate the amount of clutter in images (flowcharts, road maps, subway maps, topographic charts, weather maps and the same maps used in the current studies). C3 values for each image were highly correlated ($r = .86$) with the subjective clutter ratings. Furthermore C3 resulted in a higher correlation between subjective and C3 clutter ratings than other clutter measures (Rosenholtz, Li, Mansfield, & Jin, 2005).

The current experiments aim to demonstrate that C3 can be used to predict search efficiency in a real-world search task. Two levels of clutter are examined: the overall clutter of the image (global clutter) and the clutter of the area immediately surrounding the target (local clutter). It is predicted that global clutter will affect the preattentive stage of visual search. During the preattentive stage of visual search, potential target locations are identified based on a saliency map (Itti & Koch, 2000; Treisman, 1988; Wolfe, 1994). According to Wolfe's (2007) Guided Search model, as the complexity of the information in the display (number of distractors, distractor heterogeneity, target distractor similarity) increases, RTs increase because the number of potential target regions identified increases. We propose that the complexity of a display, and therefore the influence of the preattentive stage, can be quantified using C3's measure of global clutter.

The impact of the selective attention stage can be predicted using C3's measure of local clutter. Once potential target locations are identified, selective attention is directed to each location in order of similarity to the target (Duncan & Humphreys, 1989). As local clutter increases, the target location will be rated as less similar to the target and therefore, selective attention will arrive at the target location later in the serial search process. When the target is in a low local clutter region, attention will arrive at the target quickly regardless of the amount of global clutter because the target should be one of the most salient items. However, when the target is in a high local clutter region, the saliency rating will be lower and the target will be examined later in the serial search process. The effect of being examined later in the serial search process will be greatest for high global clutter because more potential target locations will be identified, leading to an interaction between local and global clutter. High local clutter could also slow the identification process of the target once selective attention arrives at the target location. However, this would result in a main effect of local clutter rather than an interaction between local and global clutter.

Saliency of the target and therefore, search efficiency can be influenced not only by the amount of local clutter, but also by differences between the features of the target and those of the distractors (Duncan and Humphreys, 1989). The targets in the current experiments were chosen to be similar to other visual features found in the maps, because targets with unique features often lead to a parallel search process and we are interested in the role of clutter in more complex real world search tasks. The targets and distractors are both composed of diagonal lines and dots, which are common features in the maps

(see Figure 2), and the color of the target and distractors in each map was chosen to be similar to other colors found in the map[1].

Experiment 1

In Experiment 1 we tested the effects of local and global clutter on visual search in a real world search task: finding a target on a map. Maps with global clutter ratings, binned into high, medium and low categories, were used with the target placed in a high or low local clutter region. The effect of set size in a real world search task was also examined. It is hypothesized that global clutter will be a better predictor of search efficiency than set size. In addition, we predict an interaction between local and global clutter supporting a two-stage model of visual search in a real world visual search task.

Method

Participants

Forty-seven undergraduates participated for course credit. All participants had normal or corrected-to-normal vision.

Stimuli and Design

Thirty-six maps were submitted to the C3 algorithm (Lohrenz & Gendron, under review). C3 calculates global and local clutter on a scale from 0 to 12 where a clutter rating of 0 is the lowest rating (e.g., an all black image) and 12 is the highest rating. Global clutter is defined as the clutter of the entire image and local clutter is defined as the clutter of the region surrounding the target (60 x 60 pixel square around the target).

---

[1] For each map, targets and distractors are the same color. In an attempt to make them as equally salient as possible (across maps), the color was 1) similar to other feature colors in the map's color palette, and 2) selected such that the difference between the background color and the target/distractor color was approximately the same in all maps (according to the CIE de2000 color difference formula).

The local clutter regions subtended 2.9° x 2.9° and the global clutter regions subtended 28.5° x 23.2°[2].

Three factors were examined: global clutter (high, medium and low), local clutter (low and high), and set size (4, 8, and 16; see Figure 2 and Table 1). Maps were specifically selected so that there were 12 maps at each level of global clutter (see Table 1 for average global clutter ratings at each level). Two versions of each map were created by placing the target in either a low local clutter region or a high local clutter region. The target was always a single bump elevation marker (see Figure 1) and 25% of the targets were placed in each quadrant of the map. Three versions of each of the local clutter versions were then created by placing 4, 8 or 16 distractors in the maps. Distractors were randomly placed with the constraint that on average the local clutter ratings of the distractors was similar to the global clutter ratings of the map (see table 1). Therefore, all distractors remained in the same locations for the two local clutter version for each map. A one-pixel border was placed around each target and distractor to increase visibility. Maps were presented on iMacs with a 20-inch wide screen display. Each map subtended 28.5° x 23.2°, the DBs subtended $.98^{\circ}$ x $.66^{\circ}$ and the SBs subtended $.66^{\circ}$ x $.66^{\circ}$.

---------------------------Insert Table 1 Here---------------------------

Procedure

At the beginning of each trial, participants were shown the target in the center of the screen. After pressing the space bar to begin the trial, a map was presented and

[2] Visual angles were computed from a viewing distance of 35 cm, however viewing distance was not constrained.

participants found the target as quickly as possible and clicked on it with the mouse. All trials ended after 60 seconds if no response was given. After completing a practice trial and having the opportunity to ask any questions about the task, participant saw each of the 36 maps once. Within each level of global clutter, participants saw six maps (two for each set size) at each level of local clutter. Which maps were presented at each set size and level of local clutter was counterbalanced across participants. Trial order was randomized for each participant.

Figure 1: Examples of single-bump (target) and double-bump (distractors) elevation markers. The color of the targets and distractors was always the same within a map but varied across maps depending on the typical colors found in each map.

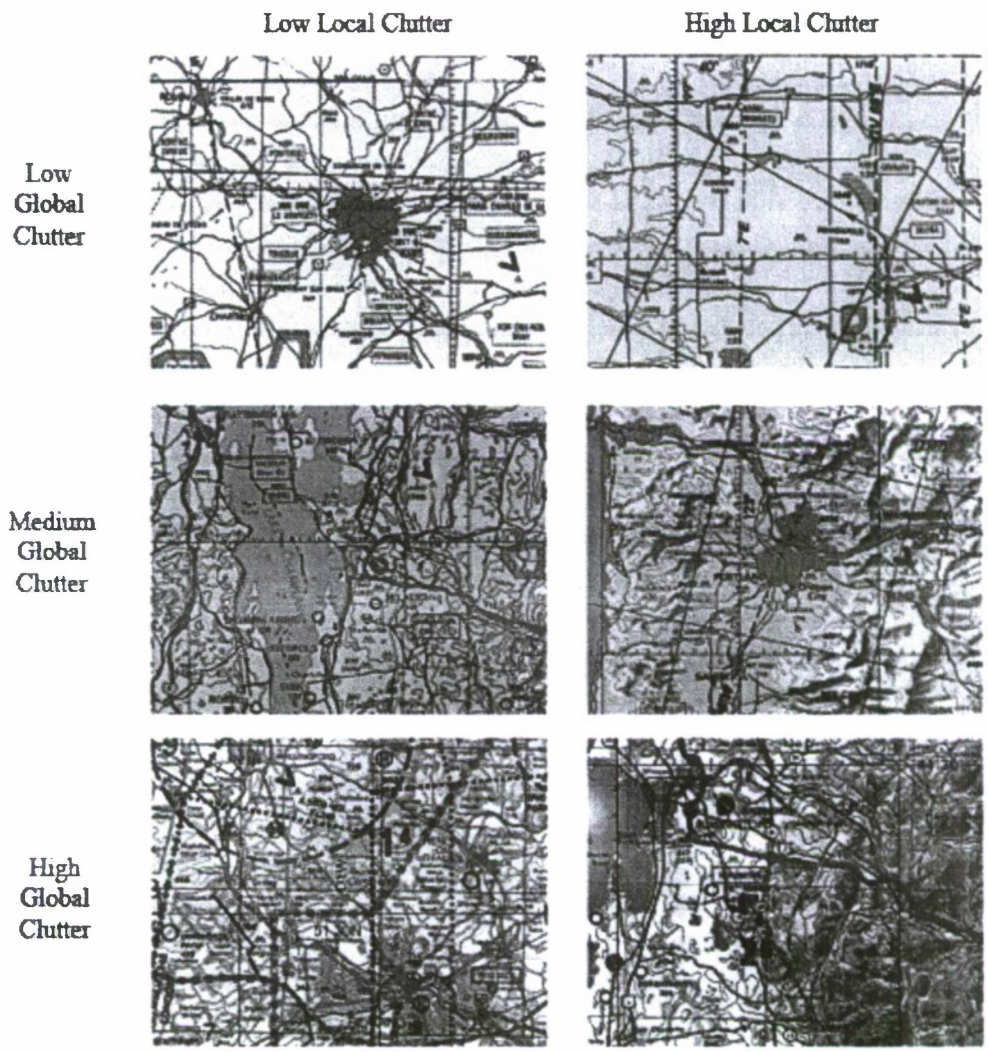

Figure 2: Examples of the maps used in Experiments 1. An example at each level of the local clutter variable and each level of the global clutter variable is provided. Black arrows indicating the targets' locations are added for the reader's benefit.

Results

A response was accurate if the mouse was clicked with a within a 17 x 17 pixel (.82° x .82°) of the center of the target within 60 seconds. Responses were given before the 60 seconds on 89% of the trials. Overall accuracy was 78% (SE = .02).

Global Clutter versus Set Size

A 3x3 repeated measures ANOVA was completed with global clutter (low, medium, high) and set size (4, 8, 16) as within-subjects factors. There was a main effect for global clutter, $F(2,86) = 75.37$, $p<.001$, $\eta_p^2 = .64$, but not for set size, $F(2, 86) = 1.28$, $p = .28$, $\eta_p^2 = .03$. The global clutter/set size interaction was not significant, $F(4, 172) = .65$, $p =.63$, $\eta_p^2 = .02$. RTs were lower for low global clutter than medium global clutter, $F(1, 43) = 109.33$, $p < .001$, $\eta_p^2 = .72$, and RTs were lower for medium global clutter than high global clutter, $F(1, 43) = 7.84$, $p = .008$, $\eta_p^2 = .15$ (see Figure 3).

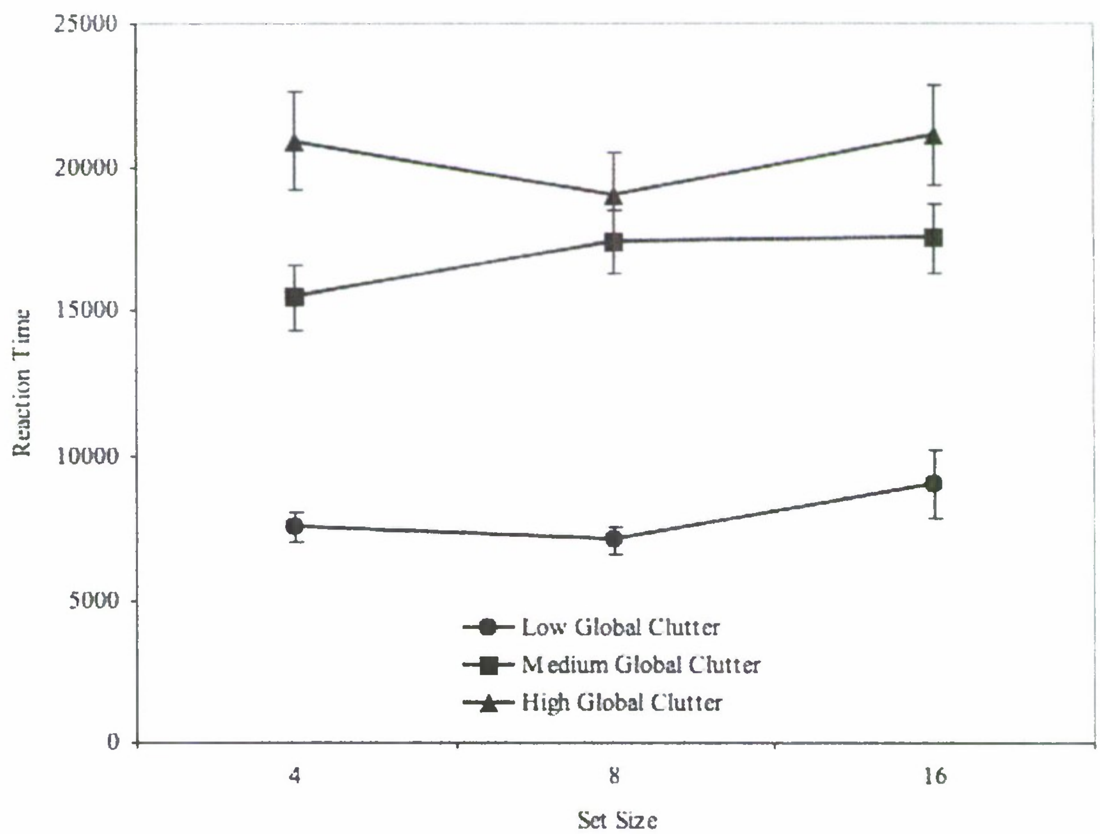

Figure 3: RTs from Experiment 2 for each level of the global clutter factor at each set size.

Global Versus Local Clutter

Data from five subjects was excluded because no accurate responses were given on high global/high local trials. A 3x2 repeated measures ANOVA was completed with global clutter (low, medium, high) and local clutter (low, high) as within-subjects factors. There was a main effect of global clutter, $F(2, 82) = 95.51$, $p < .001$, $\eta_p^2 = .7$, a main effect for local clutter, $F(1, 41) = 126.97$, $p < .001$, $\eta_p^2 = .76$, and a significant interaction, $F(2, 82) = 16.96$, $p < .001$, $\eta_p^2 = .29$. This interaction was driven by a larger effect of global clutter on RT for high local clutter than low local clutter (see Figure 4). For high local clutter, RTs increased as global clutter increased (all p-values < .001). For low local clutter, RTs also increased as global clutter increased (all p-values < .04).

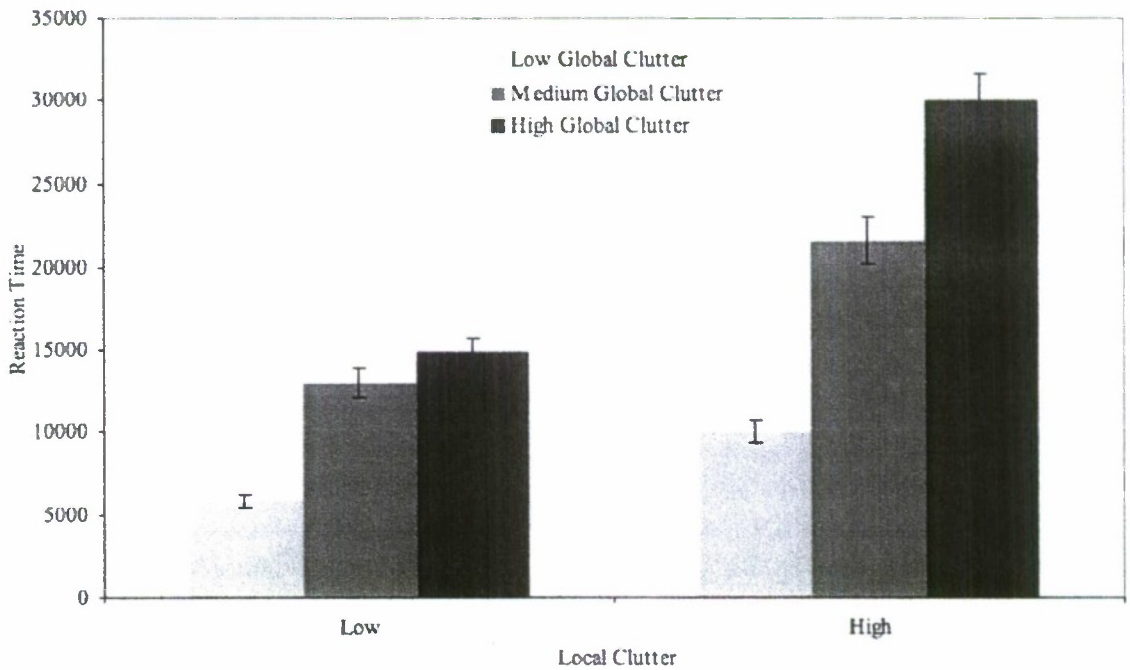

Figure 4: RTs from Experiment 1 at each level of the global clutter factor and each level of the local clutter factor.

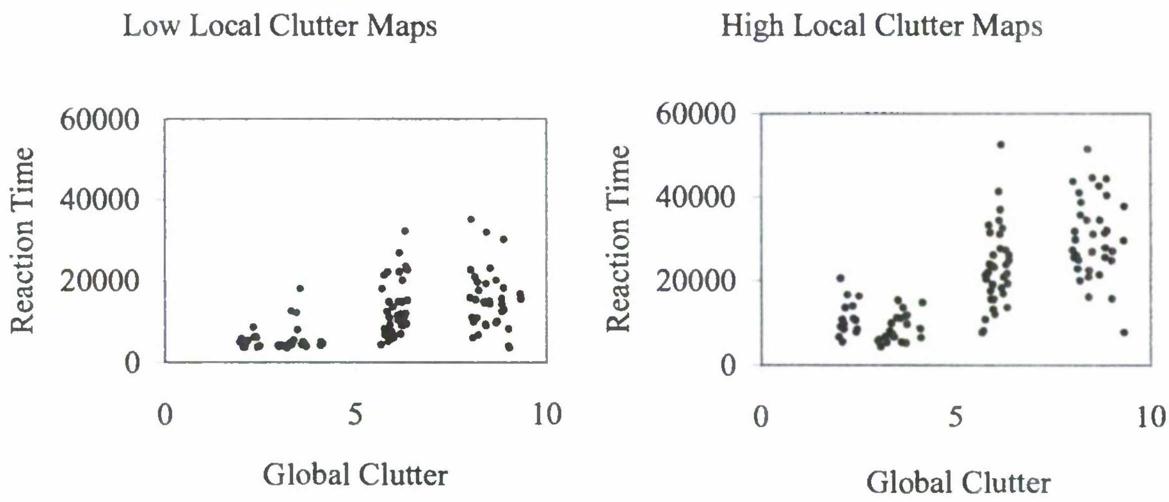

Figure 5: Reaction time plotted against global clutter for the low local clutter maps and high clutter maps in Experiment 1.

Figure 5 displays a scatter plot of reaction time plotted against global clutter for the low local clutter images and against global clutter for the high local clutter images. Global clutter accounts for 30% of the variance (slope = 1701 and intercept = 1415) in the low local clutter images and 50% of the variance (slope = 3510 and intercept = 628) in the high local clutter images. Figure 6 displays a scatter plot of reaction time plotted against local clutter (across all levels of global clutter). Local clutter accounts for 51% of the variance (slope = 3062 and intercept = 1729) in the reaction time data.

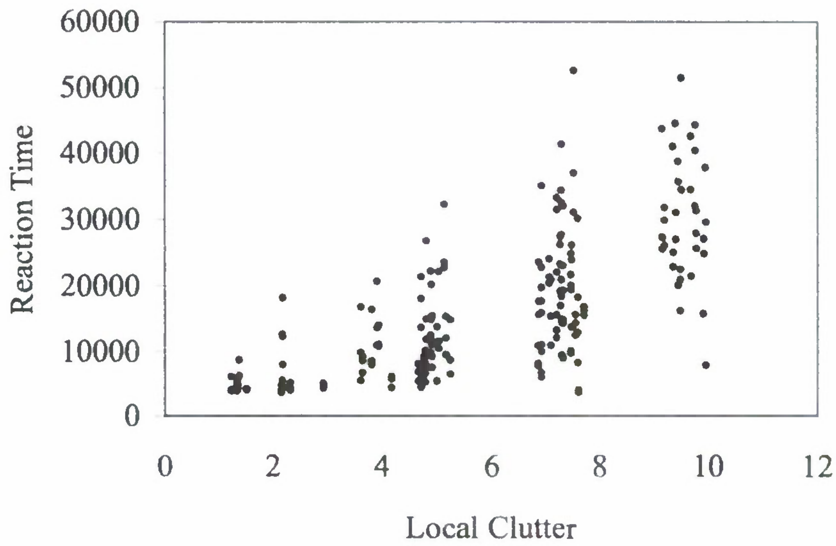

Figure 6: Reaction time plotted against local clutter for each map in Experiment 1.

Discussion

Global clutter was a better predictor of search efficiency than set size. Furthermore, the increase in RT across levels of global clutter was greater for high local clutter than for low local clutter. These results suggest that when the target is in a low local clutter region, the number of items selected during the preattentive process for inspection by selective attention has less of an impact because the target is more likely to be one of the first items examined.

Experiment 2

A control experiment was conducted to determine if the targets and distractors used in Experiment 1 lead to a set size effect when the map is removed from the display. All visual information except for the targets and distractors was removed from the images

used in Experiment 1. If serial attention is required to distinguish the targets and distractors RTs will increase as set size increases.

Methods

Participants

Fifty-five undergraduates participated for course credit. All participants had normal or corrected-to-normal vision.

Stimuli

Images from Experiment 1 were used with all visual information removed except the targets and distractors. C3 values were lower for set size 4 images ($M = .12$, $SD = .001$) than for set size 8 images [$M = .15$, $SD = .002$; $t(142) = 70.9$, $p < .001$] and C3 values were lower for set size 8 images than for set size 16 images [$M = .19$, $SD = .004$; $t(142) = 79.9$, $p < .001$].

Results

All participants responded on all of the trials before 60 seconds. Overall accuracy was 87% ($SE = .01$).

A repeated measures ANOVA with set size (4, 8, 16) as a within-subjects factor revealed a significant main effect, $F(2, 108) = 21.16$, $p < .001$, $\eta_p^2 = .28$. RTs were slower for set size 16 than set size 8, $t(54) = -2.9$, $p = .005$, and slower for set size 8 than set size 4, $t(54) = -4$, $p < .001$.

Discussion

Experiment 2 demonstrates that RTs increase with set size when no other visual information is provided. Wolfe (2007) reports a typical increase in RTs of 20 – 30 ms per item in a target present search. Here, the slope of the RT x set size function was 37.15

ms. This suggests that in the absence of visual clutter, the target and distractors used in Experiment 1 produce similar set size effects as traditionally found in serial search tasks. The C3 ratings for Experiment 2 demonstrate that clutter increases as set size increases. This further supports the use C3 as an alternate to set size for measuring of search efficiency in real world search tasks.

General Discussion

Over the past 40 years research has developed comprehensive and reliable models of visual search using highly contrived and unrealistic search stimuli. The current experiments examine the usefulness of these models in explaining search efficiency in a real world search task. The evidence presented here demonstrates that set size is difficult to use reliably to examine search efficiency in real world tasks, mainly because set size is difficult to determine. However, other measures of complexity can be used. Global clutter as measured using C3 (Lohrenz & Gendron, under review) had a positive relationship with RTs: RTs increased as global clutter increased. Global clutter affected search performance predominantly when the target was in a high local clutter region. This interaction supports a two-stage model where global clutter is important at the parallel stage of determining likely target locations and local clutter is important at the serial stage of deploying selective attention to likely clutter regions in order of similarity to the target.

The ability for local clutter as measured by C3 to predict search performance is quite impressive given the number of factors C3 does not take into account. First, C3 is a measure of bottom-up influences on search performance. It does not take into account top-down influences based on the expected properties of the target. In addition, there are

bottom-up factors that C3 does not take into account. For example, orientation and pattern entropy information are not used to calculate C3. These and other bottom-up factors are likely to play a role in visual search performance, but research has indicated that color variability is a highly important factor (Rosenholtz, et al. 2007). Our results support this conclusion by showing a relationship between search efficiency and a clutter measure based on color density and saliency. Further, our results suggest that other factors play a much smaller (perhaps negligible) role compared to color variability.

In the introduction, we discussed several factors that are likely involved in search efficiency in real world scenes: similarity, object occlusion, organization and complexity. Ideally, we would like a clutter metric that takes all of these factors into account. C3 did a good job of predicting search performance, with global clutter accounting for 50% of the variance in the high local clutter images and local clutter accounting for 51% of the variancc, but it does not necessarily account for all the important factors. Future versions of C3 will determine the influence of adding these dimensions to C3 on the ability to predict search efficiency.

Of particular interest is building a factor to account for target saliency in the C3 algorithm. In the current experiments saliency was held at a low level and was relatively consistent across levels of local and global clutter (the same target was used). It is well known in the visual search literature that a very salient target (a red T among yellow Ts) is located very rapidly regardless of the number of distractors (see Wolf, 2007 for review). The same is likely true in real world complex search tasks. If a target has a feature that is unique from everything else in the image, search time should be fast

regardless of the amount of clutter. Therefore, future versions of C3 must take into account the saliency of the target.

In conclusion, we have presented a solution to the difficulty of using set size to predict search performance in a real world search task. In addition, we have provided evidence for a two-stage model of visual search in a real world search task. These results are a very important step towards applying the extensive amount of research on visual search to real world search tasks.

Author Note

This research was funded by Naval Research Laboratory (NRL): Broad Agency Announcement grant 0748,554741 to the first author and Program Element 602435N by the NRL 6.2 Base Program to the second author.

References

Beck, M. R., & Trafton, J. G. (2007). Local spatial layout consistency affects strategies but not memory during visual search. *Journal of Vision*, 7(9), 1060.

Bravo, M. J., & Farid, H. (2004). Search for a category target in clutter. *Perception*, 33(6), 643-652.

Busey, T. & Palmer, J. (2008). Set size effects for identification versus localization depend on the visual search task. *Journal of Experimental Psychology: Human Perception and Performance*, 34(4), 790-810.

Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review*, 96(3), 433-458.

Itti, L., & Koch, C. (2000). A saliency-based search mechanism for overt and covert shifts of visual attention. *Vision Research*, 40, 1489-1506.

Lohrenz, M. C., & Gendron, M. L. (under review). A 3D clustering algorithm to model clutter in electronic geospatial displays.

Lohrenz, M. C., Trafton, J. G., Beck, M. R., & Gendron, M. L. (under review) A model of clutter for complex, multivariate, geospatial displays.

Neider, M. B., & Zelinsky, G. J. (2008). Exploring set size effects in scenes: Identifying the objects of search. *Visual Cognition*, 16(1), 1-10.

Palmer J., Ames, C.T. & Lindsey, D.T. (1993). Measuring the effect of attention on simple visual search. *Journal of Experimental Psychology: Human Perception and Performance*, 19, 108-130.

Rosenholtz, R., Li, Y., Mansfield, J., & Jin, Z. (2005). *Feature congestion: A measure of display clutter.* Presented at the Conference on Human Factors in Computing Systems, Portland, OR.

Rosenholtz, R., Li, Y., & Nakano, L. (2007). Measuring visual clutter. *Journal of Vision*, 7(2), 1-22.

Thornton, T. L. & Gilden, D. L. (2007). Parallel and serial processes in visual search. *Psychological Review*, 114(1), 71-103.

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology*, 12(1), 97-136.

Townsend, J.T. (1974). Issues and models concerning the processing of a finite number of inputs. In B. H. Kantowitz (Ed.), Human information processing: Tutorials in performance and cognition (pp. 1330168). Hillsdale, NJ: Erlbaum.

Wolfe, J. M. (1994). Guided search 2.0: A revised model of visual search. *Psychonomic Bulletin & Review*, 1(2), 202-238.

Wolfe, J. M. (1998). Visual Search. In H. Pashler (Ed.), Attention (pp. 13-73). London, UK: University College Press.

Wolfe, J. M. (2007). Guided search 4.0: Current progress with a model of visual search. In W. Gray (Ed.), Integrative models of cognitive systems (pp. 99-119). New York: Oxford.

Wolfe, J. M., Oliva, A., Horowitz, T. S., Butcher, S. J., & Bompas, A. (2002). Segmentation of objects from backgrounds in visual search tasks. *Vision Research*, 42, 2985-3004.

Table 1

Clutter values from Experiment 1

	Global Clutter	Low Local Clutter	High Local Clutter	Average Distractor Local Clutter
Low Global Clutter	3 (.7)	1.8 (.6)	4.4 (.6)	3.8 (1.1)
Medium Global Clutter	6 (.2)	4.9 (.2)	7.2 (.2)	6 (.2)
High Global Clutter	8.5 (.4)	7.3 (.3)	9.6 (.3)	8.5 (.8)

a. Standard deviations are presented in parentheses.